

# EXAMPLE OF OBJECT BASED IMAGE ANALYSIS APPLIED TO COARSE RESOLUTION IMAGES. APPLICATION TO LANDSCAPE CLASSIFICATION IN FRANCE

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## ABSTRACT

Object based image analysis (OBIA) is a powerful technique for classification of remote sensing images. Although it is generally used with very high resolution images, its application is not linked to a particular spatial resolution, and OBIA can be applied to classify coarse resolution images, such as MODIS, Meris, and the future Sentinel-3 sensor, OLCI.

In this study, a segmentation of the French landscapes is made from MODIS images, including vegetation and texture indices, by applying OBIA. Different segmentations have been generated using different segmentation parameters and input variables. Since no ground data is available for training and validating the classification, unsupervised evaluation methods are used to select the best input variables and the best segmentation parameters. The best segmentation is shown to be the one including texture indices, and leads to 84 radiometrically homogeneous regions.

From the results of the segmentation, a non supervised classification is performed and 36 different classes are identified.

## 1. INTRODUCTION

The European Landscape Convention defines the 'landscape' as an area, as perceived by people, which character is the result of the action and interaction of natural and/or human factors [1]. Landscapes are valued for a variety of reasons and provide a series of important functions, such as: sustainable use of natural resources, wildlife habitats, providing economic benefits, scenery and opens spaces, and possessing cultural heritage [2]. Since landscapes are exposed to human activities they are particularly exposed to change [2]. Identification of landscapes is important for their conservation and management.

Landscape maps already exist, however they are generally obtained from GIS data, such as topography, parent material, climate, land cover, etc. But most of these data have not a spatial and/or temporal continuity. As a consequence remote sensing can be a good alternative, since it allows obtaining continuous spatial

information with high temporal resolution (daily or more). Remote sensing has already been used in landscape mapping, specially for obtaining land cover, which is then combined with other variables, such as geological or topographical variables, for obtaining landscape maps [3].

Object based image classification (OBIA) has been widely used in recent years. This technique consists in making a first segmentation for obtaining homogeneous regions, or segments, which have additional spectral information compared to single pixels (mean value, median, maximum, minimum etc.) [4] and later classifying the regions obtained. For the segmentation, a homogeneous criterion has to be chosen. This criterion is managed by one or more parameters which can be changed, such as the scale, shape and compactness parameters in eCognition Developer 8.0 (Definiens Imaging, München, Germany).

OBIA techniques are especially useful when using very high resolution images, since at these resolution individual objects can be identified. However, OBIA is not spatial resolution-dependent, and can be applied to medium or large resolution images if the sizes of the target objects are compatible with the image resolution. To the best of our knowledge, only [5] used an OBIA approach with coarse resolution images, specifically MODIS (MODerate resolution Imaging Spectroradiometer) images, for stratifying rural landscapes in Mali.

However the use of OBIA at this broad resolution suffers from an important limitation which is the difficulty in obtaining training and validation ground data collected at the appropriate scale. Nevertheless, unsupervised evaluation methods can be used to select the best parameters of the segmentation.

This work presents an OBIA technique applied to a MODIS image time series at 250 m spatial resolution. The objective is to obtain a classification of the landscapes of the French territory.

To do this, the territory is first segmented in radiometrically homogeneous regions. Different sets of image-based variables (vegetation indices, texture indices), and different segmentation parameters are tested. The evaluation and comparison of these segmentations are then performed using methods of unsupervised evaluation.

## 2. UNSUPERVISED SEGMENTATION EVALUATION

As stated in [6] a good segmentation should accomplish these four conditions: (a) the regions must be uniform and homogeneous, (b) the interior of the regions should be simple, without many holes, (c) adjacent regions must present significantly different values for uniform characteristics, and (d) boundaries should be smoothed and accurate. Based on these criteria, the measures useful for analysing the performance of a segmentation are the homogeneity of the regions and the disparity between regions. Several methods have been used for obtaining these measures over segmentations obtained using different homogeneity criteria. By comparing these measures in the different segmentations, the best one can be chosen.

[7] proposed a function,  $F$ , based on empirical studies which measures the homogeneity of the segmented regions, the formulation included the size of the image, the number of regions segmented, the area and the average colour error of each region (defined as the sum of the Euclidean distances between the RGB colour vectors of the pixels of each region and the colour vector attributed to the region).

[8] proposed two revised functions of  $F$ :  $F'$  and  $Q$ . The new functions used the same variables as those used in  $F$  but with a different formulation.

[9] proposed a specific method for remote sensing images which included analysis of spatial autocorrelation, their base criteria was that each segment should be internally homogeneous and should be distinguishable from its neighbourhood, so the objective of the function proposed is to maximize intra-segment homogeneity and intersegment heterogeneity, which means it includes two terms, the intra-segment variance of the regions and Moran's  $I$  autocorrelation index which measures how similar a region is to its neighbours [10]. The best segmentation will be that with lower intersegment Moran's index and lower intra-segment variance.

[11] made a revision of different methods for evaluating segmentations, and they tested some of these methods. Most of the methods analysed included a measure of intra-region homogeneity and a measure of inter-region

heterogeneity, but these measures were performed differently in each method, and also the way of combining these two measures is different.

[12] used a method similar to [9] but they obtained the variance and the Moran's  $I$  index for three spectral bands (NIR, red and green) and then they calculated the average value.

[13] proposed a new unsupervised evaluation method based on intra-segment homogeneity and intersegment heterogeneity. For the first measure they used a modified version of Borsotti's equation ( $Q$ ), and for the second one they used the normalized variance of a mean feature vector of all regions which analyses the difference of the mean spectral value of a region in a band and the mean value of all the regions in the same band. They compared this method to a previous one based on entropy measures, presented in [14], and to one presented in [15]. They applied all three methods to a QuikBird image (including four spectral bands) of an urban region and they used a supervised method as a basis for comparison. They obtained a similar performance between their method and the supervised one, although they observed that the method did not identify the best segmentation but identified a segmentation with high quality, while the other methods analysed had a very different performance and did not succeed in identifying a good segmentation.

All the methods proposed for segmentation evaluation are tested over high or very high resolution images. In the present work some of these methods for evaluating segmentations are tested over coarse resolution images (MODIS). In this sense, different segmentations have been analysed by using some of the previous methods of evaluation of segmentations.

## 3. STUDY AREA AND DATA

The study area is the continental French territory as well as Corsica Island.

MODIS sensor was chosen as it offers a good agreement between spatial and temporal resolution for application to a regional scale. This sensor captures daily images, but most of the products provide temporal compositions of several days (8 and 16) with atmospherically corrected data.

The vegetation indices product of MODIS (MOD13Q1) provides the NDVI (Normalized Difference Vegetation Index) and the EVI (Enhanced Vegetation Index) at 250 m spatial resolution and 16-day temporal resolution. Images are captured daily and a 16-day synthesis is performed and provided in this product. The vegetation indices allow studying the phenology and structure of

the vegetation. But for landscape mapping, the arrangement of the elements in the surface is also important; in this sense a set of texture measures can be useful. For obtaining textures, angular effects are important, that's why the Nadir BRDF-Adjusted Reflectance product (MCD43A4) was chosen, since it provides reflectances corrected by the angular effects in 8 different spectral bands, with a spatial resolution of 500 m and temporal resolution of 8 days.

The period of study comprises 5 years (2007-2011).

## 4. METHODOLOGY

### 4.1. Pre-processing of the images

The first thing was applying the quality band of both MOD13 and MCD43 products in order to avoid including erroneous pixels in the study.

Since the final objective of the work is to obtain a classification of the French territory in radiometrically homogeneous landscapes, it is important to analyse the vegetation indices from the whole year. In order to avoid the effects of climate variation between years, a synthesis was obtained using the images of the five years of product MOD13. An image for each month was computed as the average of the images of that month for all the years (fig.1).

For obtaining the texture indices, MCD43 images were used. We first calculated EVI images, and monthly images were obtained by averaging the images of each month for all the years. Two texture images, homogeneity and entropy, were obtained from the EVI images using a 5x5 pixels window. Finally the texture images were rescaled to the same pixel size of the MOD13 images (250 m).

### 4.2. Image segmentation

Image segmentation was performed using the 'multi-resolution segmentation' algorithm available in eCognition Developer 8.0 (Definiens Imaging, München, Germany). This algorithm is a region merging technique which starts with each pixel forming an object and keep merging the regions until the homogeneity criterion (defined by the scale parameter) is achieved [16]. This scale parameter, linked to the input data, influences the size of the output segments, bigger scale parameters producing bigger regions.

Different sets of segmentations were obtained using different input variables (vegetation and texture indices). For the textural indices (homogeneity and entropy), 4 dates were chosen, from a visual analysis, as representative of the different phenological states (fig.2); April, May, August and November.

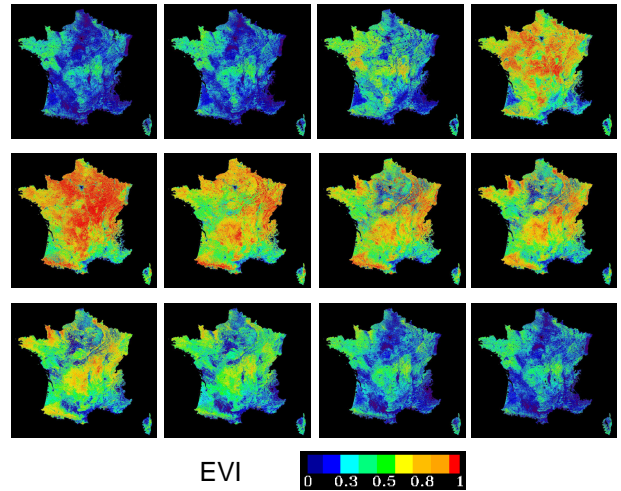


Figure 1. EVI maps obtained from MOD13 product corresponding to the monthly averaged images.

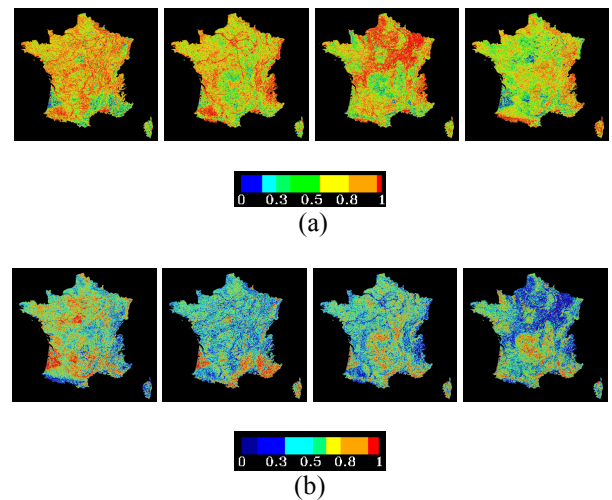


Figure 2.a) Entropy, and b) Homogeneity maps obtained from the EVI for four months (April, May, August and November).

For each combination of the input variables, 11 different values of the scale parameter were tested (between 20 and 70, in steps of 5).

### 4.3. Evaluation of segmentation

For evaluating the different segmentations obtained and choosing the best of them, two unsupervised methods were applied:

a) The method applied in [12] which uses the variance (V) as the measure of intra-segment homogeneity and Moran's index (M) as the inter-segment disparity.

$$V = \sum_{i=1}^n a_i v_i / \sum_{i=1}^n v_i \quad (1)$$

$$M = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\left( \sum_{i=1}^n (y_i - \bar{y})^2 \right) \left( \sum_{i \neq j} w_{ij} \right)} \quad (2)$$

$$J = V_{norm} + M_{norm} \quad (3)$$

where  $n$  is the total number of regions,  $v_i$  and  $a_i$  are the variance and area of region  $i$ ,  $w_{ij}$  is a measure of the spatial proximity (is equal to 1 if the regions are neighbours and 0 if not),  $y_i$  is the mean spectral value of region  $i$  and  $\bar{y}$  is the mean spectral value of the image.  $V_{norm}$  and  $M_{norm}$  are the normalised values of  $V$  and  $M$ .

b) The method proposed in [13] which uses a modification of Borsotti's equation for measuring the intra-segment homogeneity (T), and proposes a new formula for measuring the inter-segment disparity (D).

$$T = \frac{1}{10S} \sqrt{n} \sum_{i=1}^n \left( \frac{e_i}{1 + \log a_i} \right) \quad (4)$$

$$D = \left( \sum_{b=1}^n \sum_{i=1}^n (m_{ib} - mm_b) / n \right) / \sqrt{n} \quad (5)$$

$$Z = T + \lambda D \quad (6)$$

$$\lambda = (T_{max} - T_{min}) / (D_{max} - D_{min})$$

where  $S$  is the image size,  $e_i$  is the Euclidean distance between the value of each pixel in region  $i$  and the average value assigned to the region,  $m_{ib}$  is the average value of band  $b$  in region  $i$ , and  $mm_b$  is the average value of all regions in band  $b$ .  $T_{max}$ ,  $T_{min}$ ,  $D_{max}$  and  $D_{min}$  are the maximum and minimum values of  $T$  and  $D$  over a set of segmentations obtained with different homogeneity criterions.

For each of the segmentations obtained, these methods were applied. In the case of Johnson's method [12], the values of  $V$  and  $M$  were obtained for each band used in the segmentation (each image) and then the average values were obtained. In the case of Zhang's method [13] the sum of  $T$  over all the bands was obtained since in  $D$  the sum over all bands is performed. The better

segmentation is that which leads to the minimum value of these functions ( $J$ ,  $Z$ ).

#### 4.4. Classification

For obtaining the classification, the mean values of each segment were obtained and this value was assigned to the entire segment. The mean values were obtained for each variable used for obtaining the segmentation (vegetation and textural indices). The Iterative Self-Organizing Data Analysis Technique (ISODATA) from the ENVI software (Exelis Visual Information Solutions, Boulder, Colorado) was used for obtaining the classification. This technique consists in arbitrarily selecting a set of starting points and iteratively clustering them by using the Euclidean distance. The points are allocated to the cluster whose centroid is the closest [17]. The iterations stop when the assignment of points to clusters stays unchanged [17].

The parameter to adjust in this classification algorithm is the maximum number of classes to be obtained which was set equal to the number of segmented regions.

### 5. RESULTATS

#### 5.1. Segmentation

Fig. 3 and 4 present the results of the methods of [12] and [13] for the two combinations of variables which followed a trend as the works revised in the bibliography. The first one (fig.3) corresponds to the results of the segmentation obtained by using only the EVI from product MOD13. In the second one (fig.4), two textures (homogeneity and entropy) over 4 dates (April, May, August and November) are used in combination with the 12 EVI images.

In fig.3, Johnson's method shows that the best segmentation is the one obtained with a scale parameter of 50, while the Zhang's method shows similar values for scales between 30 and 50.

In fig.4, Johnson's method has a clear minimum at scale 40, which coincides with the minimum obtained when using Zhang's method, although in the case of Zhang's the minimum is not so clear as in Johnson's.

Since Johnson's method analyses the disparity between neighbour regions, we consider this method more interesting for the present study, since the biggest difficulty is in objectively defining the limits between landscapes. Although the results are similar for both methods, the Johnson's method seems to be more accurate. This was the expected result since in [13] they conclude that their method did not give strictly the best segmentation but one with high quality.

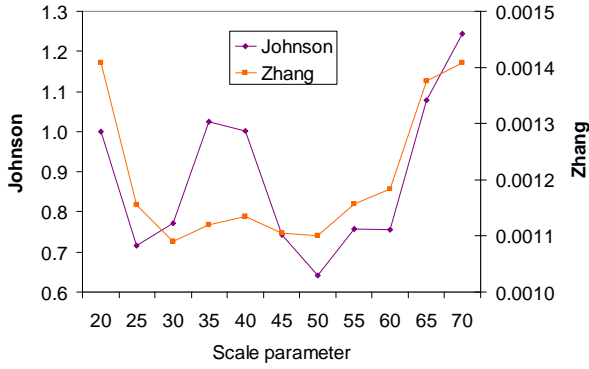


Figure 3. Quality of the segmentations of EVI images in function of the scale parameter used in eCognition.

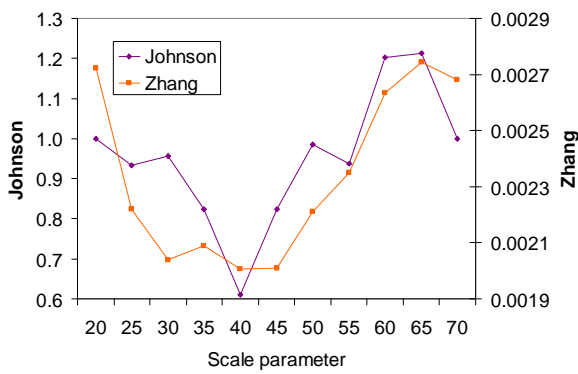
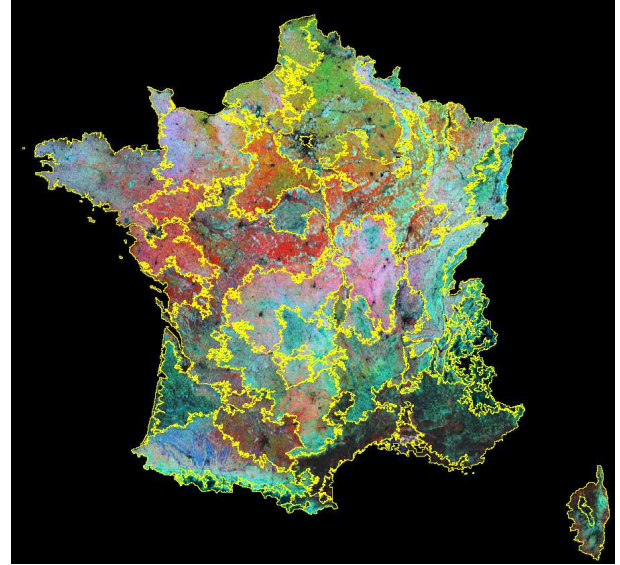


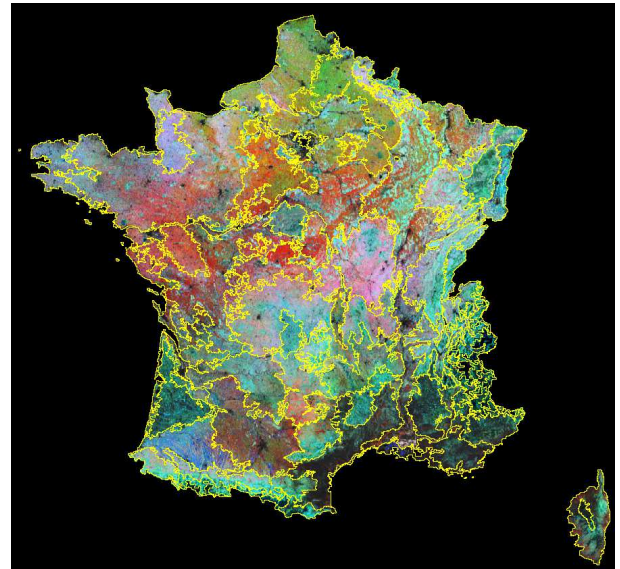
Figure 4. Quality of the segmentations of EVI and texture (homogeneity and entropy) images in function of the scale parameter used in e-Cognition.

Fig.5 shows the segmentations obtained using the both combinations of input variables, fig. 5a including 12 images of EVI and fig. 5b combining these EVI images with textures, obtained with scale parameters of 50 and 40 respectively, as these were the best scales according to Johnson's method. In the first case 61 regions were obtained, while in the second one there are 84 regions. In fig. 5 the segmentation results are superposed to a RGB composition image of EVI for different months (R: April, G: June, B: August), which allows observing the temporal evolution of the vegetation index along the months represented.

For selecting one of the two segmentations obtained we focused on [18] where different segmentation methods were analysed. In order to choose the best method they compared the form of the curves obtained with the different scale parameters, and they considered that the best method was the one which had a more pronounced valley. In the present work, the segmentation which has bigger amplitude of the curves of both variables analysed ( $J$  and  $Z$ ) is the one using textures.



(a)



(b)

Figure 5. Segmentations obtained from: a) twelve images of EVI, b) twelve images of EVI and two textures (homogeneity and entropy) obtained for four dates each.

## 5.2. Classification

Using the segmentation obtained from the EVI and the two texture indices with a scale parameter of 40, the average values of these indices was obtained for each region. With this data, an unsupervised classification was performed using the ISODATA algorithm. The classification obtained is shown in fig.6. The number of classes produced by this algorithm is 36 out of 84 regions. Some neighbour regions have been merged, and other regions which are separated in space are



assigned to the same class. In fig.6 the segmentation is superposed to the classification, allowing to see the regions that have been merged.

Fig.6 represents the radiometrically homogeneous landscape classification of the French territory.

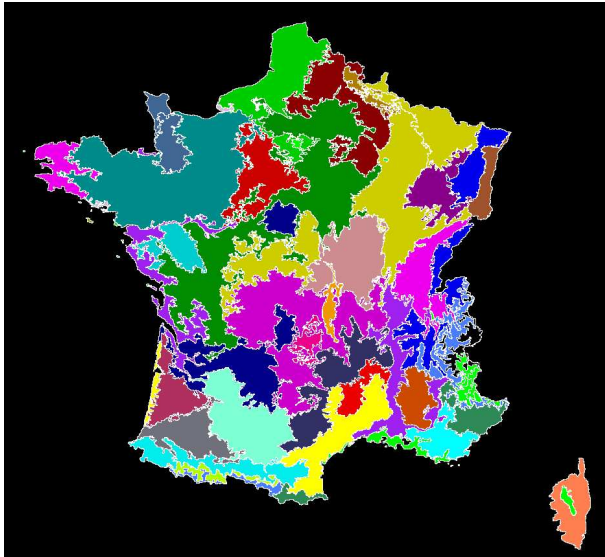


Figure 6. ISODATA unsupervised classification of the French territory in radiometrically homogeneous regions.

## 6. CONCLUSIONS

The application of OBIA for segmenting coarse resolution images (MODIS) has been tested using eCognition Developer 8.0. The methodology applied is based on spectral information (vegetation indices), temporal information (by using monthly images) and textural information which serve as a measure of the arrangement of the elements.

Different segmentations have been obtained using various sets of combinations of the input variables (vegetation and texture indices in different dates).

For each combination of variables a range of scale parameters is used (from 20 to 70, in steps of 5) and two methods of unsupervised evaluation of the segmentations (Johnson's and Zhang's) are applied. The best segmentation is the one where regions present a higher degree of homogeneity together as being different from their neighbours. The evaluation showed that the best segmentation is the one obtained by using 12 EVI images, 4 homogeneity images and 4 entropy images, with a scale parameter of 40. This conclusion remarks the importance of including texture indices in the analysis, since the vegetation indices alone have a limited capacity of distinguishing different landscapes, however the inclusion of texture in order to taking into

account the arrangement of the landscape, and the inclusion of these textures in different months, is a valuable information for segmenting the territory in homogeneous regions.

From the segmentation selected as the best one 84 regions were identified. The average values of all the input data (vegetation and texture indices in the different dates) were calculated over each of the 84 regions. These average values served as the input data for doing an unsupervised classification (ISODATA) with the ENVI software. The resulting classification leads to a map of radiometrically homogeneous landscape of France composed by 36 different classes.

Further analysis is being made in the selection of the most significant input variables (analysing other texture indices) and dates, by means of an attribute selection process, which takes into account the temporal character of these variables. This process could reduce the dimensionality of the problem by identifying the most relevant images for segmenting the landscape.

In order to obtain a landscape map of the French territory, the classes have to be characterized by means of typical landscape indicators, such as climate, topography, land cover, land use, etc.

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